# Constraining uncertainties in lake thermal responses to global climate change using an ensemble of models

# Projecting lake thermal responses to global climate change using an ensemble of models and partitioning uncertainties

## Abstract

Oligotrophic lakes provide valuable ecosystem services, yet their clear-water trophic state is increasingly at risk due to human impacts, which are expected to worsen over the next 100 years. However, the uncertainty surrounding how the climate will continue to change and how lake thermal budgets will respond leaves stakeholders such as researchers, ecosystem managers and lawmakers questioning the weight of these projections as they pertain to the real-world. Using the representative concentration pathway (RCP) 8.5 scenario coupled with four general circulation models (GCMs), an ensemble modelling approach using 5 general lake models will be applied to the northern oligotrophic Lake Sunapee. The output of the ensemble model will include temperature profiles and ice coverage from 1986 to 2099. Using these projections, insights regarding the thermal budget of Sunapee will be discussed such as stratification strength and depth, mixing, and water column temperature. Ice coverage projections will be presented and discussed as well. The outputs of the ensemble models will include sufficient information to carry out uncertainty propagation in relation to climate model uncertainty, parameter uncertainty, ecosystem model process uncertainty, and climate scenario uncertainty. The results of this study will be relevant to both stakeholders of Lake Sunapee as well as climate modelers and researchers.

## Introduction

Due to human activities, freshwater ecosystems around the globe are increasingly changing(Hering et al., 2010). Clear water, or oligotrophic, lakes provide critical ecosystem services such as drinking water and cultural and economic value yet are experiencing relatively abrupt and severe water quality problems attributed to climate change and land development(Ward et al., 2020), which is expected to continue to threaten lake ecosystems.(Ward et al., 2020) Because of this, new tools to predict future water quality are vital to improving the management of oligotrophic lakes and combat water quality degradation. However, predicting future lake water quality leaves considerable uncertainty regarding how humans will continue to impact climate, how climate will change in response to human-induced drivers, as well as how lake ecosystems will respond to climate forcing. New methods which incorporate all of these sources of uncertainty are critical to informing our understanding of future lake ecosystems.

Uncertainty is a critical aspect of predicting ecological systems. When producing predictions, it is important for scientists to understand the “weak points” in the materials and methods. This allows researchers to focus resources on constraining the largest uncertainties in a study, thereby improving their models and their predictions.(Raiho, Dietze, Dawson, Rollinson, & Tipton, 2020) For example, Raiho et al. (2020) found that process uncertainty was a large factor of uncertainty within the majority of their models, pointing to a need for models that more accurately predict the latent state of an ecological system.(Raiho et al., 2020) Gaining insight into the predictability of ecology makes ecology more relevant to policy, management and decision making. It also impacts the data collected, how models are structured, and the statistical tools linking models to data.(Dietze, 2017) The following study will require propagating the contributions of model parameters, lake ecosystem model processes, and climate model projections.(Thomas, Jersild, Brooks, Thomas, & Wynne, 2018)

Thermal stratification in lakes is an important driver of physical, chemical and biological processes in lakes and reservoirs, including complete water turnovers,(Yankova, Neuenschwander, Köster, & Posch, 2017) deep-water oxygen levels, (Jankowski, Livingstone, Bührer, Forster, & Niederhauser, 2006)(Piccolroaz & Toffolon, 2018) atmospheric gas exchange, (Tranvik et al., 2009)(Read et al., 2012) primary production(Leach et al., 2018), and quality of fisheries habitats (Hansen, Read, Hansen, & Winslow, 2017),.(Stetler et al., 2020) As climate change alters the thermal budget of lakes through increased water surface temperatures(Woolway et al., 2019), one response is a shift in mixing regimes. Particularly in northern lakes, we are seeing a shift from multiple mixing annually (polymictic and dimictic) to a single mixing event (monomictic and meromictic).(Kirillin, 2010) Changes in mixing regimes can have important implications for the ecosystem and community services which oligotrophic lakes provide, including drinking water. Processes such as primary production, fish habitation and atmospheric gas exchange and lake turnover could shift dramatically if mixing regimes shift from the status quo. In addition, ice cover is expected decrease an average of 29 +- 8 days under RCP 6.0 conditions.(Woolway & Merchant, 2019) The implications of this finding are especially important as lake ice coverage is increasingly understood to be relevant for both summer and winter lake ecology.(Salonen, Leppäranta, Viljanen, & Gulati, 2009)(Hampton et al., 2017)

However, there is considerable uncertainty in how global climate will continue to change in the future. First, there is uncertainty in how societies will response to global climate change and curb carbon emissions which drive changes in climate. As a result, there are several representative concentration pathway (RCP) scenarios which combines assumptions about multiple ecological and sociological factors, including high population, slow income growth, and modest technological change and energy intensity improvements. (Riahi et al., 2011) This study uses the RCP 8.5 scenario, which assumes that greenhouse gas emissions continually increase over time, leading to a radiative forcing (the additional amount of energy in Earth’s climate system) of 8.5 W/m2 at the end of the century. The RCP 8.5 scenario is the most aggressive and adopts a “business as usual” attitude from the current emission outputs, which is the best match out to midcentury and likely further under current and stated policies. Under RCP 8.5, end of century warming outcomes range from 3.3 C to 5.4 C globally.(Schwalm, Glendon, & Duffy, 2020) In order to represent the effects of various climate scenarios, global general circulation models (GCMs) are needed, which model Earth’s atmosphere using the radiative and thermodynamic properties of the atmosphere as well as the frictional dissipation and dynamics of kinetic energy on multiple scales. (Phillips, 1956) However, among GCMs there can be disagreement in how various global climate variables will respond(Pirtle, Meyer, & Hamilton, n.d.), resulting in uncertainty about the directionality of future climate change.

Uncertainty surrounding how lake ecosystems will respond to changes in climate is also a major barrier to understanding how climate change will affect lake thermal budgets. One way to estimate uncertainty in lake thermal processes is to use a suite of different lake models. The LakeEnsemblR R package is one tool which can be used to predict lake thermal budgets using a suite of models. Using multiple lake models to predict the same scenario allows us to XYZ. The package includes five different lake models, all of which use different methods of estimating lake thermal properties. These lakes include FLake (Freshwater Lake model) which simulates lake systems using a two-layer parametric representation focusing on heat budget, GLM (General Lake Model) which applies a lagrangian structure to replicate mixing dynamics, GOTM (the General Ocean Turbulence Model) which is a vertical 1D hydrodynamic water column model, MyLake (Multi-year Lake simulation model) which simulates daily vertical profiles of water temperature, seasonal ice and snow cover as well as others, and Simstrat, which is a vertical 1D hydrodynamic model combining a buoyancy-extended k-epsilon model with seiche parameterization.(“LakeEnsemblR: An R package that facilitates ensemble modelling of lakes,” n.d.) By predicting lake thermal properties using a suite of lake models, we can better estimate the range of uncertainty in future lake responses to climate change. Studies of this nature that partition uncertainty are few and far between, and virtually nonexistent concerning individual lakes and their future projected outcomes.

In this study, we aim to take a novel approach to quantifying the numerous uncertainties involved in lake thermal projections. We aim to couple a global climate scenario with four general circulation models to estimate global climate model uncertainty. Further, we will estimate lake ecosystem model uncertainty by coupling our global climate model output with five lake models in LakeEnsemblR to make projections of lake thermal dynamics nearly a century into the future, up to 2099.

## Materials and Methods

In order to better quantify the uncertainty surrounding how lake thermal dynamics will respond to climate change, we will use one future climate change scenario representative concentration pathway (RCP 8.5) to drive four general circulation models (GCM), couple with five lake thermodynamic models within LakeEnsemblR. Using a 30+ year historical dataset, parameters within LakeEnsemblR will be calibrated, and historical baselines will be created for each GCM by propagating past climate conditions and carbon dioxide concentration into the future. GCM climate data will then be forced through the calibrated LER and anomalies will be calculated as the difference between the calculated historical baseline projections and the projected values according to RCP 8.5 conditions. Anomalies between GCM’s will then be compared using 30-year intervals up to 2099. We will assess changes to lake thermal properties by calculating anomalies from the historical average for thermocline depth, length of stratification, thermocline strength, and ice coverage. An array of compiled outputs including parameter distributions, water column output, and anomaly values can subsequently be used to partition uncertainty across the climate models, parameters, lake models, total forecast and climate scenario.

*Study Site*

Lake Sunapee is an oligotrophic, clear-water lake located between Merrimack and Sullivan Counties in New Hampshire, USA (Figure 1). (Ward et al., 2020) The lake is dimictic, with ice cover ranging from December or January-March or April.(Bruesewitz, Carey, Richardson, & Weathers, 2015) The mean thermocline maximum depth is 6-8 m(Carey et al., 2014). Further, the Lake Sunapee region has experienced a rapid increase in observed air temperature, at a rate of 0.42 C per decade from 1979 to present.(Ward et al., 2020)

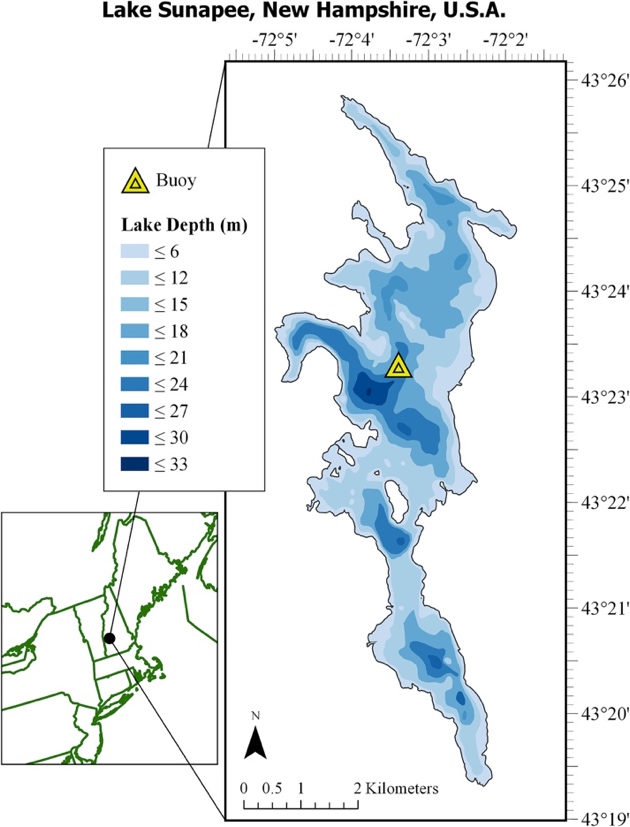


Figure 1: Location and Bathymetry of Lake Sunapee, New Hampshire, USA. Taken from Ward et al.

*Data*

Historical observations for Lake Sunapee will be used, including inflow and outflow data collected from 1981-2020, hypsography data, and water temperature data collected from 1986-2020 . The ERA-Interim data Merged and Bias-corrected for ISIMIP(EWEMBI) meteorological forcing data (years?) will be used in place of locally collected meteorological data in order maintain consistency when using the GCMs in a post-calibrated LER setup.

*General Circulation Models*

The EWEMBI corrected general circulation models (GCMs) MIROC5, IPSL-CM5A-LR, GFDL-ESM2M, and HADGEM2-ES will be used under RCP 8.5 conditions for the purposes of future projections within Sunapee. These GCMs are bias corrected climate model projections from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), which uses community-defined scenarios with standardized climate variables and socioeconomic projections as inputs. (Ruane et al., 2017)

*Calibration and Evaluation*

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Description automatically generatedLakeEnsemblR will be calibrated using the time period 1 January 2005 to 31 December 2009 as these years cover a wide range in annual temperature and precipitation as well as contain an extensive amount of data according to Ward et al. (2020). (Ward et al., 2020) Calibration shall be carried out using a Latin Hypercube simulation (LHC) to first establish the priors of the parameters, and subsequently a Monte Carlo Markov Chain (MCMC) simulation to further establish the values of the parameters. Distributions of parameters will be used to estimate parameter uncertainty for each of the models. Models will be evaluated using Root Mean Square Error (RMSE), and will be calibrated to within 2 degrees Celsius RMSE for each of the five LER models for temperature for the whole water column. In addition to this, evaluation will include visually comparing observed and modeled stratification using a heatmap (e.g., Figure 2)

Figure 2: Thermal Profiles visualizing water column stratification in each LER model

*Model Analysis*

The LER models will be calculated by using historical climate conditions and carbon dioxide concentration using calibrated parameter values, propagating out to 2099. Once the historical projection is calculated, GCMs under RCP 8.5 conditions will be forced through LER up to 2099. Using the results of each projection, anomalies will be calculated by taking the difference between the “historical” projection and the RCP 8.5 projection within each GCM, a step that must be taken in order to compare results across GCMs. We will compare anomalies of thermal properties, including water column temperature, length of stratification, thermocline depth, thermocline strength, and ice coverage for each of the different LER-GCM combinations, resulting in a total of 20 lake model outputs (figure 3). These variables will be analyzed using 30-year intervals as this represents a climactic period, or a more complete and broad cycle that reduces climactic noise associated with using GCMs and the RCP scenarios. Once these metrics of interest have been calculated for each model over 30-year intervals, a comparative analysis between all LER/GCM model combinations will be carried out including comparing the anomalies of stratification time, thermocline depth, water column temperature and others.

Chart

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Figure 3. Scaffold structure visualizing the output of the RCP/GCM/LER combination

*Uncertainty partitioning*

*Climate Model Uncertainty*

Climate model uncertainty will be estimated by generating projections using the 5 ISIMIP models under RCP 8.5 conditions. In order to isolate climate model uncertainty from other types of uncertainties, parameter values will be held constant and process uncertainty will not be propagated. The mean estimate of all five LER models will be used to avoid uncertainty between ecosystem models. Each climate model will be assumed to be equally likely, with the metric of uncertainty being defined as the width of the 95% quantile interval of percent change in total temperature between 2010 and 2099.(Thomas et al., 2018)

*Lake Ecosystem Model Uncertainty*

LakeEcosystem model uncertainty will be estimated by generating projections across all 5 LER models from all 4 GCM models under RCP 8.5 conditions. In order to isolate ecosystem uncertainty from other types of uncertainties, median parameter values are taken from MCMC parameter calibration chains and process uncertainty is not propagated. The mean of the four ISIMIP models will be used across LER models in order to avoid uncertainty between climate models. Each ecosystem model will be assumed to be equally likely, with the metric of uncertainty being defined as the width of the 95% quantile interval of percent change in total temperature between 2010 and 2099.

*Parameter Uncertainty*

Parameter uncertainty will be estimated by sampling from the posterior distributions of the calibrated parameter sets. Using the sampled parameter sets, an ensemble will be constructed of 100 simulations from 2010-2099. To avoid interactions between parameter uncertainty and the other types of uncertainty, ensembles will be generated for each of the climate models and each of the ecosystem models. Parameter uncertainty will be calculated by taking the average uncertainty from each of these runs. Parameter uncertainty will be defined as the 95% quantile interval from the ensemble members averaged across the climate and ecosystem models.(Thomas et al., 2018)

*Ecosystem Model Process Uncertainty*

Ecosystem model process uncertainty will be calculated by using a state-space data assimilation technique using sampled water temperature vales from a normal distribution at the end of a timestep and using the values to simulate the subsequent timestep. 100 ensemble models will then be calculated from 2010-2099 using median parameter values and generating all GCM/LER combinations. In this case, ecosystem model process uncertainty will be defined as the 95% quantile interval from the ensemble members averaged across GCM/LER combinations.

*Total Forecast Uncertainty:*

Total forecast uncertainty is calculated by simultaneously propagating uncertainty from the climate model uncertainty, ecosystem model uncertainty, parameter uncertainty and ecosystem model process uncertainty. Assuming that each model is equally likely, simulations from each model will be combined into a single distribution. The metric of uncertainty will be defined as the width of the 95% quantile interval from the projected output.

## Implications

This project will be multifaceted in its outcomes: first, the outputs of the LakeEnsemblR models will give insight into the future of Lake Sunapee given certain climate conditions. This will provide desired insights to managers and homeowners residing at Lake Sunapee, who are greatly interested in mitigating the impacts of climate change on their lake in order to maintain its community-wide and personal values. Second, this project will lead to novel insights revolving around the modelling itself. Because all models have inherent uncertainty, whether that be revolving around future temperature projections, global circulation methods, or water column properties, it is important for researchers to understand how much uncertainty is present and where that model uncertainty is coming from (e.g., model parameters, driver data). Because this project contains multiple models for both climate projections and lake water quality response, the ability to compare an ensemble of predictions is possible and extremely useful. These insights will be relevant to researchers and modelers carrying out similar climate change impact studies in order to mitigate future negative impacts on lake water quality.

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